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Article

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Marine pollution assessment and source mapping along the Visakhapatnam coast using remote sensing and GIS techniques

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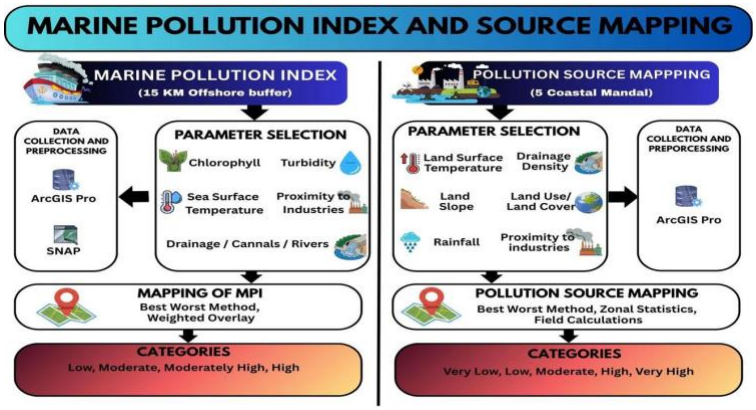

Highlights

- *Satellite and marine pollution data were integrated to map the Marine Pollution Index.*
- *Proposed GIS-based methodology for pollution risk assessment and mitigation actions.*
- *Developed Marine Pollution Index (MPI) highlighting southern Visakhapatnam areas.*
- *Urban land cover, high LST, and flat slopes drive pollutant retention in runoff areas.*
- *Identified Visakhapatnam Urban, Pedagantyada as major inland pollution contributors.*

Abstract

Marine pollution in coastal regions is a growing environmental concern, demanding integrated strategies for sustainable coastal management and spatial planning. This study assesses the spatial intensity and inland sources of marine pollution along the Visakhapatnam coast, extending from Bheemunipatnam in the north to Gangavaram in the south. A novel Marine Pollution Index (MPI) was developed using a 15 km offshore buffer zone by integrating five marine parameters Chlorophyll-a, total suspended matter (TSM), sea surface temperature (SST), proximity to industrial and port areas, and proximity to drainage systems. All datasets were harmonized to a 1 km spatial resolution and objectively weighted using the Best Worst Method (BWM), a multi-criteria decision-making approach. Results identify proximity to drains/canals (0.4158) and industrial/port areas (0.2366) as the dominant contributors to marine pollution, followed by TSM (0.1577), Chlorophyll-a (0.1183), and SST (0.0717). To link marine impacts with inland drivers, a complementary geospatial analysis incorporating seven terrestrial parameters was conducted. The results reveal Visakhapatnam Urban as the primary source region, followed by Pedagantyada and Gajuwaka, while Bheemunipatnam shows minimal influence. This integrated marine-terrestrial framework offers a transferable decision support tool for identifying pollution hotspots and guiding targeted coastal management interventions.

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1 Introduction

Marine pollution is a multifaceted and growing environmental threat, encompassing diverse contaminants such as nutrient enrichment, which triggers eutrophication alongside toxic chemicals like heavy metals and hydrocarbons, plastic debris spanning macroplastics to microplastics, and thermal stress caused by rising sea surface temperatures (Thiagarajan and Devarajan, 2025). The primary sources of these pollutants are land based and include industrial effluents, untreated sewage, storm water runoff, and agricultural inputs, which are ultimately transported into the marine environment via rivers, drains, and direct land-based discharge (Gunasekara et al., 2025). These pollutants result in several adverse environmental effects, such as oxygen depletion, harmful algal blooms, loss of biodiversity, and bioaccumulation of toxic substances in marine organisms, thereby affecting fisheries and human health (Halpern et al., 2008). Offshore waters of India, particularly in the Bay of Bengal, exacerbate these issues due to heavy monsoonal runoff that transports large volumes of sediments and pollutants from inland areas into the sea (Subramanian et al., 2023). Satellite based investigations using MODIS-Aqua and Sentinel-3 OLCI over the Visakhapatnam coast in India have revealed significant seasonal variations in sea surface temperature (SST) and Chlorophyll-a concentrations, with elevated SST during summer and post monsoon seasons leading to reduced Chlorophyll-a levels (Das, 2024). This thermal stratification hampers nutrient upwelling, resulting in diminished biological productivity (Das, 2024). In high-runoff regions, particularly near ports and drainage outfalls, turbidity levels increase substantially, inhibiting phytoplankton photosynthesis and altering aquatic productivity (Mohan et al., 2025).

Recent advances in remote sensing using multispectral satellite data from Sentinel-2 MSI (Multispectral Instrument) and Landsat-8 have facilitated the detection and quantification of floating plastic debris, identifying major accumulation zones along urban industrial coastlines such as Visakhapatnam (Nivedita et al., 2024). Additionally, microplastics have been detected in fish, shrimp, and molluscs collected from Indian coasts, including those around Visakhapatnam, raising serious concerns about their entry into the human food chain and associated toxicological risks particularly due to the adsorption of contaminants such as Polychlorinated Biphenyls (PCBs) and heavy metals (Resmi and Vaishnavi, 2025). These findings emphasize the urgent need for integrated pollution mapping strategies capable of identifying both the sources and spatial distribution of marine pollutants in vulnerable coastal regions. Visakhapatnam is recognized as a significant marine pollution hotspot due to its high density of industrial, urban, and port-related activities. The city hosts two major seaports Visakhapatnam Port, one of the oldest and busiest in India, and Gangavaram Port, a deep-water facility both of which contribute to marine contamination through ballast water discharge, oil spills, and sediment resuspension from dredging operations. Furthermore, the presence of large industrial zones, including Hindustan Petroleum Corporation Limited (HPCL), Rashtriya Ispat Nigam Limited (RINL), Coromandel International, Hindustan Shipyard Limited, and various chemical and fertilizer plants particularly in the Pedagantyada, Gajuwaka, and Malkapuram administrative sub-districts adds to the pollution burden (Indian Ports Association, 2023). Investigations by the Andhra Pradesh Pollution Control Board (APPCB) and academic institutions have reported alarming concentrations of pollutants such as nitrates, phosphates, chromium, and lead in harbor waters, with certain zones exhibiting chronic organic enrichment and low dissolved oxygen levels (Andhra Pradesh Pollution Control Board, 2022). Benthic biodiversity studies in these areas have revealed a dominance of opportunistic species near discharge outlets, indicating ecological imbalance and environmental stress due to persistent contamination (Panigrahi et al., 2025).

Microplastic pollution continues to be a growing concern, with detectable levels found in seafood species harvested along the Visakhapatnam coast. This raises the likelihood of trophic transfer, posing risks to seafood safety and increasing the potential for toxic bioaccumulation (Bhattacharya et al., 2023; Bhattacharya et al., 2025). These cumulative trends establish Visakhapatnam as a critical case for comprehensive marine pollution assessment, encompassing both offshore pollution dynamics and land-based pollution sources. Although previous studies have provided valuable insights into localized pollution in Visakhapatnam, a significant gap remains in spatially integrated evaluations that connect both marine and inland pollution sources to overall coastal pollution using a multi-criteria-based approach. Existing literature often relies on single parameters or field samples that are typically confined to port areas, thereby lacking a broader geospatial perspective and robust decision-support frameworks necessary for prioritizing high-risk zones and identifying actionable interventions (Rezvani et al., 2023). Furthermore, conventional pollution assessments in this region have adequately employed robust Multi-Criteria Decision-Making (MCDM) tools to evaluate the relative influence of diverse environmental variables. Among MCDM techniques, the relatively recent Best Worst Method (BWM), introduced by Rezaei (2015), has shown superior consistency and reduced

subjectivity compared to classical approaches such as the Analytic Hierarchy Process (AHP) for order of preference by similarity to ideal solution such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Mukherjee, 2014). Its applicability in environmental decision-making has been successfully demonstrated in studies on groundwater vulnerability assessment (Subbarayan et al., 2024), flood risk mapping (Cheah et al., 2022; Sood et al., 2025), and ecological sensitivity evaluation, due to its flexibility in handling heterogeneous environmental data. However, its use in marine pollution mapping and inland pollution source identification remains underexplored, particularly along the Indian coastline.

To address this gap, the present study proposes a twofold geospatial framework: (1) development of a Marine Pollution Index (MPI) using five critical marine indicators within a 15-km coastal buffer, and (2) inland source evaluation at the administrative sub-districts level, based on seven environmental parameters influencing pollutant discharge into the marine ecosystem. Utilizing satellite remote sensing data, geospatial analytics, and parameter weighting through BWM, this study aims to produce spatially explicit marine pollution risk maps. These outputs will support evidence-based decision making for coastal environmental governance and sustainable pollution management in the Visakhapatnam region.

2 Study area

Visakhapatnam district is located in the northeastern part of Andhra Pradesh, India, between 17°15′ and 18°32′ N latitude and around 83.2° E longitude. It encompasses an urban area of approximately 682 km² and features a coastline of about 135 km, stretching from Bheemunipatnam in the north to Pedagantyada in the south, along a critical eastern Indian trade corridor. **Figure 1** illustrates the geographical extent of the study region, highlighting key coastal administrative sub-districts and a 15 km buffer zone encompassing nearshore and offshore areas in the Bay of Bengal.

The region experiences a tropical wet and dry climate, with annual air temperatures ranging between 24 °C and 32 °C and an average annual rainfall of approximately 1,071 mm, predominantly during the southwest monsoon season (June to September) (Climate-Data.org; 1999-2024). The relative humidity averages around 67.78%, while coastal wind speeds are typically about 10 km/h, influencing sea conditions and the dispersion of pollutants (Saha, 2016).

Geomorphologically, the coastline is diverse, comprising sandy beaches, dune fields, and rocky outcrops such as Dolphin Nose and Yarada Hills, which extend from the Eastern Ghats and shape the regional drainage patterns (Das, 2022; Nagamani et al., 2022). The Gosthani River drains the area and discharges into the Bay of Bengal at Bheemunipatnam, while several urban drains and canals release untreated sewage directly into the sea, especially during the monsoon season (Dey and Majumdar, 2021). This coastal region supports ecologically sensitive nearshore waters essential for artisanal fisheries, biodiversity conservation, and natural coastal protection. However, these environments are increasingly vulnerable to pollution, eutrophication, and sediment loading due to escalating anthropogenic pressures.

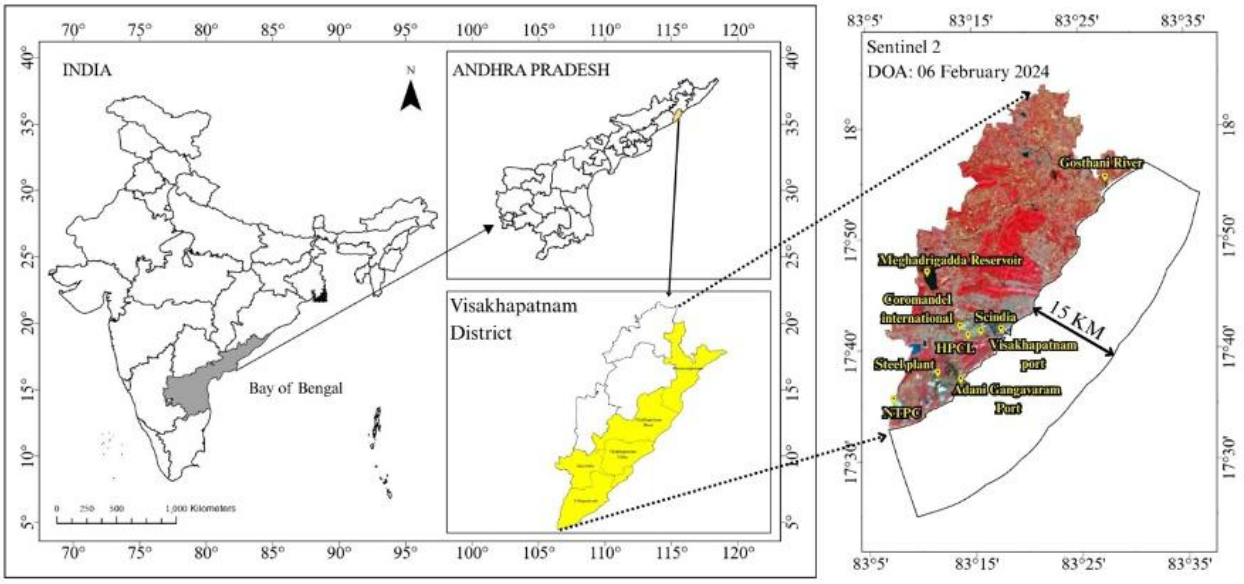

Figure 1. *Satellite image of the study area located in Andhra Pradesh state in southeast India.*

The five coastal administrative sub-district Bheemunipatnam, Visakhapatnam Rural, Visakhapatnam Urban, Gajuwaka, and Pedagantyada host significant industrial infrastructure, including the HPCL refinery, RINL steel plant, Gangavaram Port, Visakhapatnam Port, Hindustan Shipyard, and NTPC Simhadri, along with numerous chemical and fertilizer plants (APIIC) (Satyanarayana et al., 2021). These facilities substantially contribute to coastal runoff and marine pollution, as environmental monitoring has revealed elevated concentrations of heavy metals like lead and chromium in harbor sediments, and oil contamination exceeding 550 µg/L near Dolphin Nose, indicating long-term ecological stress and degradation of benthic biodiversity (Mohammad et al., 2021). Moreover, microplastics (<120 µm) have been detected in various marine organisms along the Visakhapatnam coast, indicating widespread plastic pollution with potential implications for food safety and ecosystem health (Saha et al., 2021).

3 Data used

A combination of satellite data and geospatial vector layers was used in this study to assess the level of marine pollution and land-based contributions along the Visakhapatnam coast (Pati et al., 2014; Panigrahi et al., 2025). All geospatial preprocessing tasks were performed using Sentinel Application Platform (SNAP) and ArcGIS Pro. To ensure consistency, raster datasets used for the MPI were resampled to a spatial resolution of 1 km, aligning with the 1 km resolution of the SST dataset. No resampling was applied to the layers used for administrative sub-district analysis. For MPI computation, Chlorophyll-a and turbidity data were obtained as Level 2 WFR products (S3A_OL_2_WFR) from the Sentinel-3 Ocean and Land Color Instrument (OLCI), accessed through the Copernicus Open Access Hub. The relevant bands, Chlorophyll-a and TSM, were processed in SNAP, including atmospheric correction and resampling to 1 km. The Group for High Resolution Sea Surface Temperature (GHRSST) Multi-scale Ultra high Resolution (MUR) SST dataset in NetCDF format was used to derive monthly SST data for all 12 months of 2024. These were averaged using raster calculator tools in ArcGIS Pro. Additionally, locations of industries, ports, rivers, drains, and canals were extracted from OpenStreetMap (OSM), and Euclidean distance transformations followed by reclassification were applied to generate risk-based distance zones for inclusion in the MPI.

For the administrative sub-district wise inland pollution assessment, seven datasets were prepared. Land Surface Temperature (LST) was acquired from RS-Labs based on Landsat 8 TIRS data at a 30 m resolution. Rainfall data were sourced from Centre for Hydrometeorology and Remote Sensing Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record (CHRS PERSIANN-CDR) and interpolated using the kriging method (Manini et al., 2022). Land Use/Land Cover (LULC) maps were obtained from National Remote Sensing Centre (NRSC) (https://www.nrsc.gov.in/). Drainage density, slope, and proximity maps were generated using CartoSAT DEM and OSM vector layers. Unlike MPI processing, these administrative sub-district level datasets were preserved at their native resolutions, and zonal statistics were applied to compute mean values of each parameter within the five coastal administrative sub-districts (**Table 1**).

Table 1. *The datasets utilized in this study.*

Parameter	Source	Sensor / Dataset	Spatial resolution
Chlorophyll-a	https://www.copernicus.eu/en/access-data/conventional-data-access-hubs	Sentinel-3 OLCI (CHL_NN)	300 m
Turbidity (Total suspended matter)	https://www.copernicus.eu/en/access-data/conventional-data-access-hubs	Sentinel-3 OLCI (TSM_NN)	300 m
Sea surface temperature (SST)	https://podaac.jpl.nasa.gov/GHRSST	MUR SST (Multi-scale Ultra Resolution)	1 km
Land surface temperature (LST)	https://rslab.gr/Landsat_LST.html	Landsat 8 TIRS	30 m
Rainfall	https://chrsdata.eng.uci.edu/	Satellite–Gauge Blended Product	~25 km (native)
Drainage density	https://bhuvan-app3.nrsc.gov.in/data/download/index.php	CartoSAT-1 (via Bhoonidhi)	30 m
Slope	https://bhuvan-app3.nrsc.gov.in/data/download/index.php	CartoSAT-1 (via Bhoonidhi)	30 m

4 Methods

4.1 Marine pollution index (MPI) and pollution source mapping (PSM)

A MPI was developed based on five spatial parameters: Chlorophyll-a, turbidity, SST, distance to industries/ports, and distance to drains, rivers, and canals, to evaluate marine pollution along the Visakhapatnam coastline. ArcGIS Pro was used to delineate a 15 km coastal buffer that defined the study area. The satellite products were pre-processed and atmospherically corrected using the SNAP software provided by European Space Agency (ESA), and then resampled to a uniform spatial resolution of 1 km. The SST data, available in NetCDF format as monthly composites for the year 2024, were averaged using the raster calculator in ArcGIS Pro to generate a single representative SST layer. Distance-based layers for land-based pollution sources such as ports, industries, drains, and canals were derived using OSM data. Euclidean distance transformations were applied within 5 km buffers for industrial and port areas and within 2 km buffers for drains, canals, and rivers, generating continuous raster surfaces representing proximity.

All five parameters were standardized to raster format with a 1 km resolution. To integrate these diverse datasets, a MCDM approach using the BWM was applied, enabling weighted overlay analysis and the creation of the final MPI raster. This raster layer indicates spatial variations in pollution levels within the coastal buffer zone. The geospatial outputs of this analysis are presented in methodology flowchart (**Fig. 2**), which includes both original and reclassified layers of each parameter. Each of the five MPI input parameters was reclassified into five ordinal pollution categories ranging from 1 (very low) to 5 (very high), based on their respective pollution influence levels (**Table 2**). To support visual interpretation, ten sub-panels: (a) Chlorophyll-a (original), (b) Chlorophyll-a (reclassified), (c) Turbidity (original), (d) Turbidity (reclassified), (e) SST (original), (f) SST (reclassified), (g) Drain proximity (original), (h) Drain proximity (reclassified), (i) Industry proximity (original), and (j) Industry proximity (reclassified) were presented (**Fig. 3**).

The final step in the development of the MPI involved the application of the BWM, a structured MCDM technique used to determine the relative importance (weights) of the five selected parameters. A pairwise comparison was conducted to evaluate the influence of each parameter relative to both the best and worst criteria. The standardized optimal weights, derived using the BWM solver, indicated that proximity to drains/canals had the highest weight (0.4157), followed by proximity to industries/ports (0.2366), turbidity (0.1577), Chlorophyll-a (0.1183), and SST (0.0717)

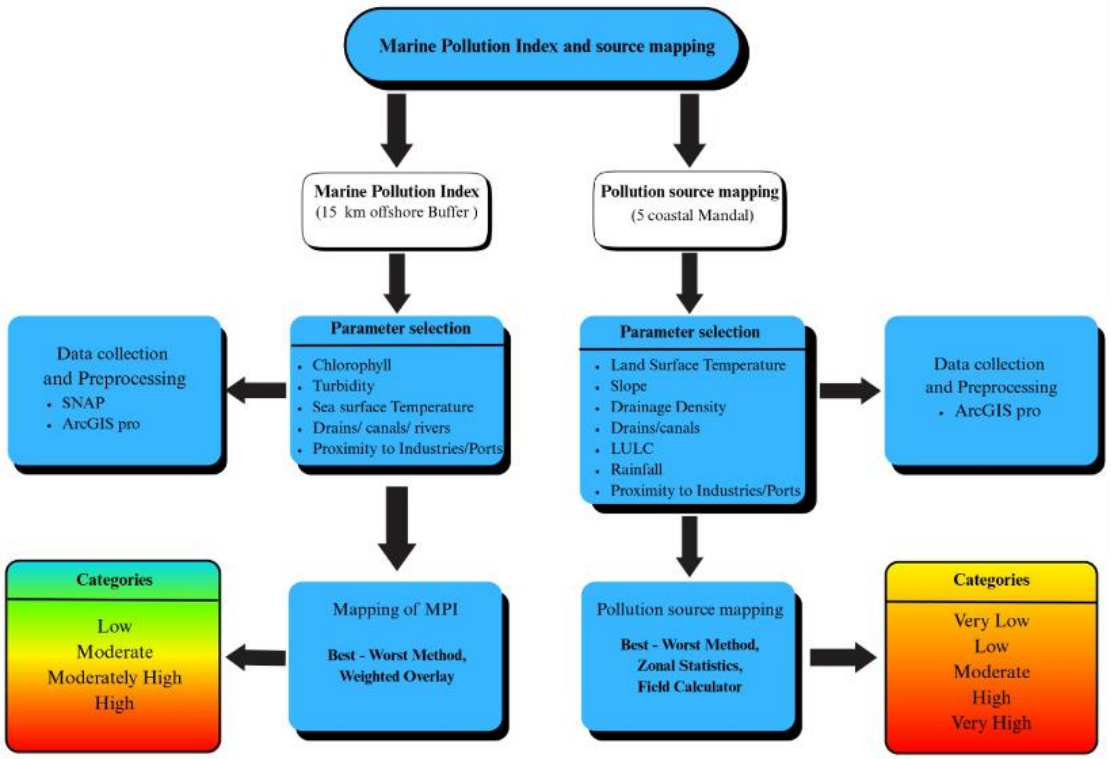

Figure 2. *Methodological framework for the development of the Marine Pollution Index (MPI) and coastal pollution source mapping.*

Table 2. *Reclassification of MPI parameters.*

Parameter	Original value	Reclassified classes	Pollution level
Chlorophyll-a (mg/m³)	0.247–14.8	0.2–1	Very low to very high
		1–3	
		3–5	
		5–10	
		10–14.8	
Turbidity (NTU)	0.017–25.3	0–5	Very low to very high
		5–10	
		10–15	
		15–20	
		20–25.3	
SST (°C)	28–28.3	<28.1	Minimal to severe risk
		28.1–28.16	
		28.16–28.22	
		28.22–28.28	
		>28.28	
Distance to drains (m)	0–5,000	0–1,000	Severe to minimal
		1,000–2,000	
		2,000–3,000	
		3,000–4,000	
		4,000–5,000	
Distance to industries (m)	0–5,000	0–1,000	Severe to minimal
		1,000–2,000	
		2,000–3,000	
		3,000–4,000	
		4,000–5,000	

(**Table 3**). These weights were subsequently used in a weighted overlay analysis in ArcGIS Pro to generate the MPI map, which spatially represents the intensity of marine pollution within the 15 km coastal buffer zone. Importantly, the consistency ratio (CR) was calculated to be 0.2, which is below the acceptable threshold of 0.2306, thereby confirming the reliability of the assigned weights.

To assess inland sources of marine pollution along the Visakhapatnam coast, source mapping at the administrative sub-districts level was conducted for five coastal administrative sub-districts: Visakhapatnam Urban, Visakhapatnam Rural, Gajuwaka, Pedagantyada, and Bheemunipatnam. These were extracted from a district level shapefile. This includes identifying seven environmental and anthropogenic variables likely to influence the transport of pollutants into the coastal marine system. The variables included: LST, LULC, annual rainfall, slope, drainage density, proximity to drains/canals/rivers (within 2 km), and proximity to industries/ports (within 5 km).

Raster based datasets such as LST (from Landsat 8 TIRS), slope (derived from DEM), and rainfall (from CHRS PERSIANN-CDR) were reclassified, and zonal statistics were applied using administrative sub-districts polygons as analysis zones. Proximity layers for drains/canals and industries/ports were converted into Euclidean distance raster and similarly reclassified. LULC was generated through supervised classification of satellite imagery, while drainage density was derived from digitized layers based sourced from Swarna Latha and Nageswara Rao (2011). Mean values for each parameter were extracted at the administrative sub-districts level using the Zonal Statistics in ArcGIS Pro and subsequently joined to the administrative sub-district shapefile on a parameter-by-parameter basis. This approach enabled a geospatial evaluation of the relative influence of

Table 3. *Weights derived using BWM for MPI parameters.*

Parameter	Weight
Drain/canals	0.4158
Industries/ports	0.2366
Chlorophyll-a	0.1183
Turbidity	0.1577
SST	0.0717

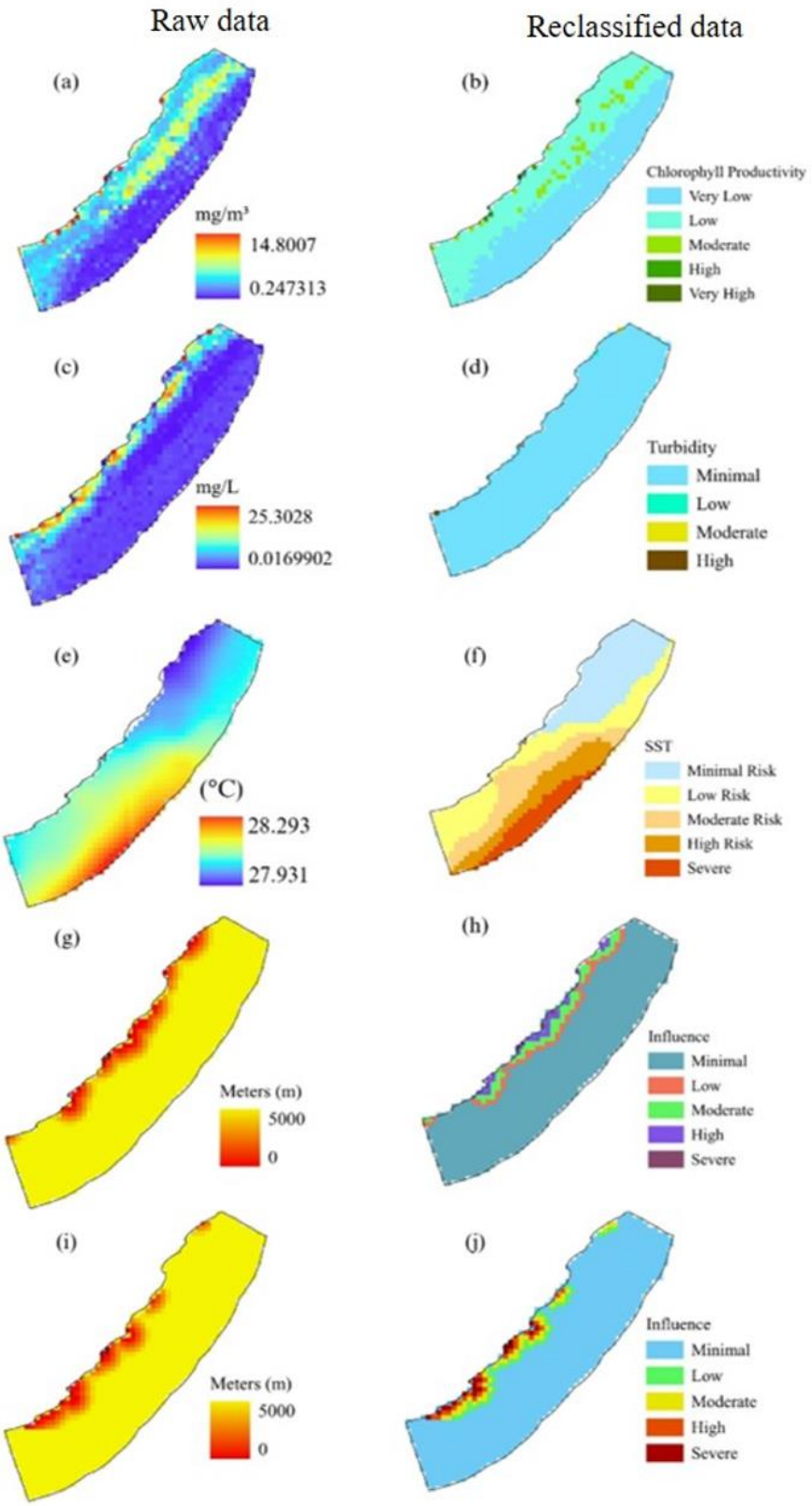

Figure 3. *Original and reclassified rasters of Chlorophyll-a (a and b), turbidity (c and d), sea surface temperature (e and f), drain proximity (g and h), and industry proximity (i and j) for MPI, respectively.*

each variable within the five administrative sub-districts and prepared the dataset for integration into a MCDM framework using the BWM. To ensure comparability and facilitate integration into a unified decision-making

framework, all seven raster datasets were reclassified into five standardized pollution potential classes ranging from "minimal" to "very high" based on their relative contribution to inland marine pollution (**Table 4**).

Rainfall values ranging from 1,500 mm to 1,718 mm were categorized into different classes, where low rainfall areas (1,500–1,535 mm) were considered to have very high pollution potential due to limited surface runoff dilution, while regions experiencing more frequent rainfall events exhibited minimal pollution potential due to enhanced dilution and flushing, areas with infrequent rainfall were associated with higher pollution potential; however, intense rainfall events, particularly flash floods, can enhance surface runoff and lead to increased transport of contaminants into aquatic systems. The slope, extracted using CartoSAT DEM, ranged from 0° to 90° and was reclassified such that flat areas (0–5%) were identified as zones of very high pollutant deposition, whereas steeper slopes posed a lower risk of pollutant accumulation. LST values, ranging from 0 °C to 48 °C, were reclassified into five intervals. Temperatures exceeding 42 °C was designated as urban heat island zones, indicating a higher likelihood of thermal discharges, which contribute to elevated pollution levels. Drainage density, varying between 0.001 and 17.95 km/km², was also reclassified into five categories for instance, values between 0–3.5 were considered minimal, while values exceeding 14 indicated very high pollution potential. This is because areas with higher drainage density provide more pathways for pollutants to reach coastal waters. For proximity to drains and canals, Euclidean distance was calculated within a 2 km buffer and divided into five classes: areas within 0–400 m were classified as having very high influence, while those within 1,600–2,000 m were considered to have negligible impact. Rainfall events especially flash floods can lead to increased aquatic contamination.

Similarly, proximity to industries and ports was analyzed using a 5 km buffer zone and classified into four categories: 0–1,000 m (very high), 1,000–2,000 m (high), 2,000-4,000 m (moderate), and 4,000–5,000 m (minimal) pollution influence (**Table 4**). Urbanization was used as a proxy variable to reclassify the LULC data, wherein urban and built-up areas were assigned the highest pollution potential scores due to their association with industrial activity and surface runoff. Each of the reclassified raster layers was subsequently summarized at the administrative sub-districts level using zonal statistics, allowing for the extraction of mean values for each parameter within the five coastal administrative sub-districts (**Fig. 4**). These outputs were then used to generate thematic maps, which were combined into a composite visual to illustrate the spatial distribution and variability of pollution contributing factors across the study area. This approach provided an integrated view of how different

Table 4. *Reclassification of inland parameters.*

Parameter	Original value	Reclassified classes (Pollution potential)
Rainfall (mm)	1,500–1,718	Very high: 1,500–1,535; High: 1,535–1,570; Moderate: 1,570–1,605; Low: 1,605–1,640; and Minimal: 1,640–1,718.
Slope (%)	0–90	Very high: 0–5; High: 5–20; Moderate: 20–40; Low: 40–60; and Minimal: 60–90.
LST (°C)	0–48	Minimal: 0–26; Low: 26–30; Moderate: 30–35; High: 35–42; and Very high: 42–48.
Drainage density	0.001–17.95	Minimal: 0–3.5; Low: 3.5–7.0; Moderate: 7.0–11; High: 11–14; and Very high: 14–17.95.
Proximity to drains (m)	0–2,000	Very high: 0–400; High: 400–800; Moderate: 800–1,200; Low: 1,200–1,600; and Minimal: 1,600–2,000.
Proximity to industries (m)	0–5,000	Very high: 0–1,000; High: 1,000–2,000; Moderate: 2,000–3,000; Low: 3,000–4,000; and Minimal: 4,000–5,000.
LULC (urbanization proxy)	Multiple classes	Very high: Urban/built-up; High: Semi-urban; Moderate: Agriculture; Low: Vegetation; and Minimal: Water bodies/barren.

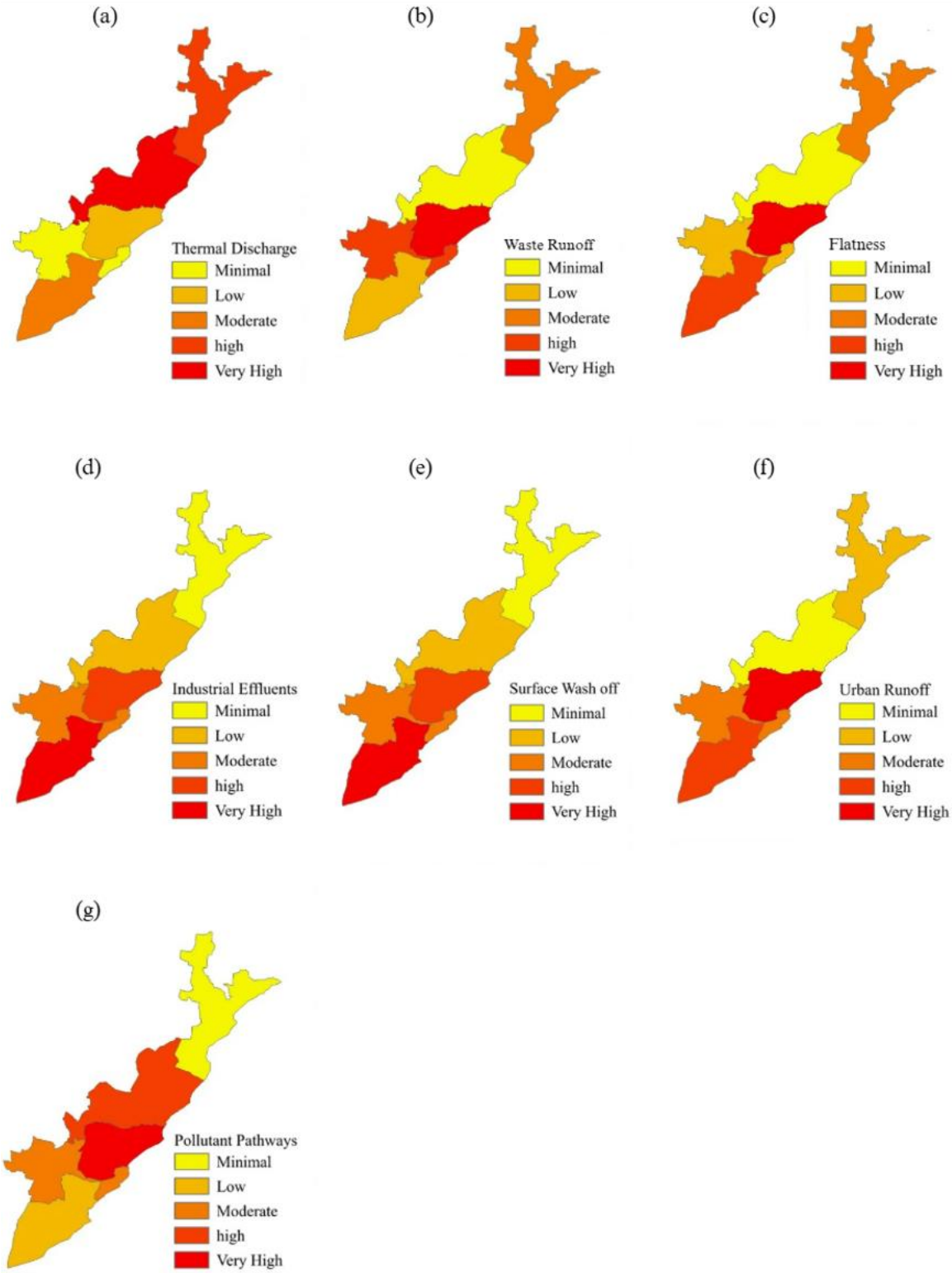

Figure 4. *Inland contribution of various pollution causing sources.*

environmental and anthropogenic parameters influence inland sources of marine pollution along the Visakhapatnam coast.

After the reclassification and zonal statistical aggregation of all seven parameters, the BWM was employed to assign objective weights to each contributing factor, incorporating

expert judgment and the relative significance of each parameter. The BWM formulation produced the following normalized weights: proximity to drains/canals/rivers (33.24%), proximity to industries/ports (20.59%), LST (14.12%), rainfall (11.76%), drainage density (8.83%), LULC (7.36%), and slope (4.12%) (**Table 5**). These weights were applied in a weighted overlay analysis using ArcGIS Pro, in which the normalized administrative sub-districts level scores were integrated to generate a composite pollution contribution index. The ensuing map categorized the five coastal administrative sub-districts into five categories, i.e., minimal, low, moderate, high, and very high inland contribution to marine pollution.

4.2 Best Worst Method (BWM)

The BWM is a relatively recent and effective MCDM approach, developed to determine optimal weights for decision criteria using fewer and more consistent pairwise comparisons. The BWM demonstrates superior performance compared to traditional methods such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and SMART, by reducing the cognitive load on decision-makers while increasing the consistency and reliability of the outcomes (Rezaei, 2015). In BWM, the first step involves listing all the decision criteria, which includes the five marine pollution indicators for the MPI and the seven inland contributing factors for the administrative sub-districts level analysis. Expert judgment is then applied to identify the best (most important) and the worst (least important) criteria among them. Following this, two preference vectors are constructed: the Best-to-Others (BO) vector, which expresses the preference of the best criterion over all others (rated on a scale of 1 to 9), and the Others-to-Worst (OW) vector, which indicates the extent to which each criterion is preferred over the worst one.

In Eq. 1 a_{Bj} denotes the preference of the best criterion B over criterion j, over the worst criterion W. These preferences are derived from a predefined comparison scale (typically 1 to 9). The goal of the BWM is to determine the optimal weights w_j^* for each criterion such that the maximum deviation from the pairwise comparisons is minimized. This is formulated as a linear optimization model as follows:

$min\ \xi$ is subject to

$$\xi, w_j$$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \le \xi,\ \left|\frac{w_j}{w_W} - a_{jW}\right| \le \xi,\ \sum_j w_j = 1,\ w_j \ge 0,\ \forall j \quad (1)$$

Here, ξ represents the maximum absolute deviation from the pairwise comparisons, and minimizing it ensures that the derived weights are as consistent as possible with the provided judgments. Once the optimal value of ξ is obtained, the consistency ratio (denoted as K_{si}) is calculated to assess the level of consistency in the decision-maker's judgments. It is defined as Eq. 2.

$$K_{si} = \frac{\xi}{CI_{\max}} \quad (2)$$

The smaller K_{si} the more reliable judgments are. In comparison with AHP, which demands $n\ (n-1)/2$ comparisons, BWM only uses 2 $n-3$ comparisons that decreases the possibility of inconsistency. In addition, it does not use fractional inputs, which make the calculations simple. These advantages have seen BWM used extensively in several fields, such as supply chain evaluation, priority setting regarding wastewater reuse, logistics performance evaluation and sustainability evaluation (Yucesan et al., 2021). Even though the BWM needs less comparison than the AHP, it is based on the same premise of pairwise preference ratings. AHP adopts the Saaty scale (Saaty, 2013), which is a basic 1–9 (1 indicates equal importance, 2 represents a level between equal and moderate importance, 3 denotes moderate importance, 4 indicates a level between moderate and strong importance, 5 represents strong importance, 6 indicates a level between strong and very strong importance, 7 denotes very strong importance, 8 represents a level between very strong and extreme importance, and 9 indicates extreme importance) scoring that enables the decision-makers to indicate the strength of importance between the criteria.

Although BWM follows the same numerical range, they simplify it by narrowing the scope of the comparison to only

Table 5. *Derived weights using BWM for inland.*

Parameter	Weight (%)
Drains/canals/rivers (proximity)	33.24
Industries/ports (proximity)	20.59
Thermal discharge (LST)	14.12
Rainfall	11.76
Drainage density	8.83
Urban runoff (land use)	7.36
Slope	4.12

the best and worst criteria, not all possible pairwise comparisons.

5 Results

5.1 Indicators of marine pollution

5.1.1 Chlorophyll–a concentration

Chlorophyll-a is used as an indicator of phytoplankton biomass and serves as a proxy for nutrient enrichment and organic pollution in marine waters. Nutrient fluxes particularly nitrogen and phosphorus from agricultural runoff, sewage, and greywater stimulate algal growth, which can lead to oxygen depletion and ecosystem imbalance. The highest recorded Chlorophyll-a concentration was 14.8 mg/m³, particularly in the waters near the Meghadrigedda outfall, the southern port basin, and along the coasts of Malkapuram and Gajuwaka, indicating localized eutrophication (**Fig. 3b**). The central coastal regions, such as RK Beach, showed moderate Chlorophyll-a levels, while the northern waters remained relatively unpolluted. The BWM assigned a weight of 0.1183 to this parameter, highlighting its role as a biological indicator of pollution hotspots. The spatial distribution of elevated Chlorophyll-a near drainage outlets and urban areas further supports its utility in identifying zones of nutrient loading and organic contamination.

5.1.2 Turbidity

Turbidity is a measure of the concentration of suspended solids in coastal waters, including sediment particles, organic matter, and waste debris. These materials limit light penetration and interfere with primary productivity, and are typically associated with surface runoff, port dredging, and the discharge of wastes. Turbidity values derived from the Sentinel-3 dataset ranged from 0.017 to 25.30 NTU (**Fig. 3d**). Areas with high turbidity levels (>20 NTU) were predominantly observed in the port-adjacent waters of Gangavaram, the inner harbor region, and at drain outfalls along the southern part of Visakhapatnam. These zones were classified as high to very high in the MPI. Turbidity received a moderate weight of 0.1577 in the BWM framework, as it serves as both an aesthetic and ecological indicator of water quality degradation. The spatial distribution of high TSM values aligns with areas experiencing increased sediment loading due to anthropogenic activities particularly dredging and maritime operations reinforcing its relevance in identifying environmentally stressed marine zones.

5.1.3 Sea surface temperature

SST is an indicator of the thermal condition of seawater and is influenced by both natural climatic fluctuations and thermal discharges from local industries and power plants. SST values ranged from 301.08 to 301.44 K (27.93°C to 28.29°C), with slightly elevated temperatures observed near Gangavaram Port, the HPCL refinery coast, and the eastern industrial waterfronts (**Fig. 3f**). Although the variation in SST is relatively small, localized increases can stress aquatic organisms, reduce dissolved oxygen levels, and exacerbate other pollution related effects, such as algal blooms. The BWM assigned the lowest weight (0.0717) to this parameter, indicating that, while SST contributes to overall ecological stress, it has a comparatively limited standalone impact relative to chemical or biological indicators. Nevertheless, the spatial correspondence between areas of slightly elevated SST and zones of high industrial activity supports its inclusion in the MPI model.

5.1.4 Drains, canals and rivers

This parameter represents the proximity of marine areas to major inland drainage features, including canals, storm drains, and river mouths. These hydrological conduits are primary pathways for the discharge of untreated sewage, urban runoff, and industrial effluents into the marine environment. A 2 km Euclidean distance was calculated using the OSM drainage network, and the resulting distances were reclassified into five zones of influence. Regions located within 0−1,000 m of drainage outlets particularly along the southern coast near the Meghadrigedda drain outlet, Malkapuram, and Yarada were associated with very high MPI values (**Fig. 3h**). These areas were characterized by dense outfalls, which directly correlated with peak pollution levels. Elevated concentrations of Chlorophyll-a and turbidity were also observed at these sites, further confirming the accumulation of pollutants. The dominance of this parameter as a pollution driver is quantitatively supported by the BWM, which assigned the highest weight (0.4158) to proximity to drains, emphasizing its critical role in marine pollution along the Visakhapatnam coast. The significant influence of this factor is further validated by the strong spatial overlap between regions with short distances to drainage networks and areas exhibiting high MPI scores.

5.1.5 Proximity to industries and ports

The largest sources of marine pollution are the industrial and port areas due to the discharge of chemical effluents, oil spills, thermal discharges, and coastal realignment activities. Using OSM layers, a 5 km Euclidean buffer was created

around all major industries and ports in the region, and the resulting distance zones were reclassified accordingly. Gangavaram Port, Hindustan Shipyard, and the industrial zones of Pedagantyada and Gajuwaka fall within the high-risk buffer range of 0–2,000 m and show strong spatial overlap with areas of high MPI. These zones are closely associated with port operations, thermal outflows, and logistics-related activities, all of which contribute significantly to deteriorating water quality. The BWM assigned a weight of 0.2366 to this parameter, indicating its substantial role in driving coastal pollution. Observed anomalies in SST and elevated turbidity concentrations near these regions align with the expected impacts of industrial activity, further confirming the critical importance of this parameter within the MPI framework (**Fig. 3j**).

5.2 Inland parameters

5.2.1 Land surface temperature

The highest mean LST was recorded in Visakhapatnam Urban, Gajuwaka, and Pedagantyada, with temperatures in built-up areas reaching up to 48°C. These regions exhibited similar patterns of high pollution contribution, indicating a strong correlation between urban heat, surface imperviousness, and pollutant accumulation. With a weight of 0.0981 LST serves as a reliable indicator of anthropogenic heat signatures and the intensity of urbanization affecting marine ecosystems (**Fig. 4a**).

5.2.2 Proximity to drains and canals

Visakhapatnam Urban administrative sub-district was found to have the highest inland contribution to marine pollution, primarily due to its proximity to a dense drainage network (**Fig. 4b**). Areas located within 1,000 meters of major drains particularly those near the Meghadrigedda outfall were predominantly classified in the "very high" pollution category. Another high-risk area was Pedagantyada, where the density of drain outfalls closely overlaps with industrial zones. This spatial distribution aligns with the 0.3324 weight assigned to the proximity-to-drains parameter, reinforcing the conclusion that drainage-linked flow paths are the most dominant inland sources of marine pollution along this coastal stretch.

5.2.3 Slope

The slope analysis indicated that Visakhapatnam Urban, Pedagantyada, and Gajuwaka are located in areas with low slopes (0–5%), which promote stagnation and surface retention of pollutants (**Fig. 4c**). These regions corresponded with areas of high pollution contribution, whereas Bheemunipatnam and Visakhapatnam rural characterized by steeper slopes consistently exhibited lower pollution levels. Although slope was assigned the lowest weight (0.0401) in the analysis, its spatial influence was evident in controlling terrain driven runoff behavior.

5.2.4 Proximity to industries and ports

The highest inland pollution scores were observed in Pedagantyada, Gajuwaka, and parts of Visakhapatnam Urban, particularly in areas located within 2 km of major industrial settlements and port facilities. These zones are adjacent to significant pollution emitters such as Gangavaram Port, HPCL, and the Vizag Steel Plant, which consistently place them within the high to very high pollution categories (**Fig. 4d**). The influence of industrial activity is effectively captured by this parameter, which contributes 0.2059 to the overall inland pollution index highlighting its role as a robust source of marine pollution, particularly in southern Visakhapatnam.

5.2.5 Rainfall

The lowest annual rainfall values were recorded in Visakhapatnam Urban and Rural administrative sub-districts, with 1,500 mm and 1,717 mm, respectively. Although rainfall is a natural phenomenon, it enhances the transport of pollutants during surface runoff, particularly in urbanized areas (**Fig. 4e**). Regions that experienced both high rainfall and high drainage density such as Visakhapatnam Urban and Pedagantyada exhibited clear inland-to-marine pollution pathways. This parameter, which was assigned a weight of 0.0657, was found to be significant, especially when interacting with other variables such as slope and land use.

5.2.6 Urban runoff

An increased pollution index score was observed in administrative sub-districts with predominant urban land cover, particularly Visakhapatnam Urban and Gajuwaka. These regions are largely impervious, limiting infiltration and thereby intensifying pollutant-laden runoff. In contrast, Bheemunipatnam exhibited greater green cover, resulting in lower pollution index values. The spatial analysis supports the assigned weight of 0.1176, highlighting the significance of LULC as a key factor contributing to urban pollution loading (**Fig. 4f**).

5.2.7 Drainage density

The results of the drainage density analysis indicated that Visakhapatnam Urban administrative sub-districts exhibited the most saturated drainage network compared to

Pedagantyada. Flat and low-lying built-up areas recorded higher line density values, facilitating more efficient runoff transport. These administrative sub-districts ranked highest in the pollution contribution index. Drainage density emerged as a critical terrain-based proxy for pollutant mobility toward the coast, with a weight of 0.1402 assigned in the multi-criteria analysis (**Fig. 4g**).

6 Discussion

6.1 Spatial distribution of marine pollution index

The spatial output of the MPI reveals that the southern coastal regions of Visakhapatnam specifically the areas surrounding Gangavaram Port, Visakhapatnam Harbour, and the Meghadrigedda drain outlet are categorized as zones of very high pollution (**Figs. 1 & 5**). This classification is supported by elevated values of Chlorophyll-a concentrations (>10 mg/m³), turbidity (>20 NTU), and sea surface temperature values ranging between 28°C and 29°C. These locations lie within 1 km of major drainage outlets and within 2 km of industrial and port activities, which received the highest weights in the BWM model (0.4158 and 0.2366, respectively). Moderate to high pollution levels were also observed along central urban coastal stretches such as Rama Krishna Beach, Tenneti Park, and Rushikonda, likely influenced by storm water runoff, tourism pressure, and urban effluent discharge. In contrast, the northern coastal region off Bheemunipatnam shows relatively lower pollution intensity, except for moderate to high MPI values near the Bheemunipatnam river outlet, where moderate to high MPH values are likely driven by agricultural runoff and sediment laden river inflows.

Similar spatial patterns of coastal marine pollution have been documented globally, particularly near major ports, river mouths, and urbanized coastlines. Studies from East Asia, Europe, and North America report elevated Chlorophyll-a, turbidity, and thermal anomalies associated with nutrient enrichment from riverine discharge, industrial effluents, and port-related activities, leading to localized eutrophication and degraded water quality (Islam and Tanaka, 2004; Halpern et al., 2008; Landrigan et al., 2020). The consistency of these global observations with the present study highlights the broader applicability of the MPI framework for identifying pollution hotspots influenced by land-based anthropogenic pressures. The MPI shows strong positive correlations with Chlorophyll-a (r = 0.85), sea surface temperature (r = 0.84), turbidity (r = 0.87), and the observed pollution index (r = 0.86), indicating that higher MPI values reliably capture increased biological productivity,

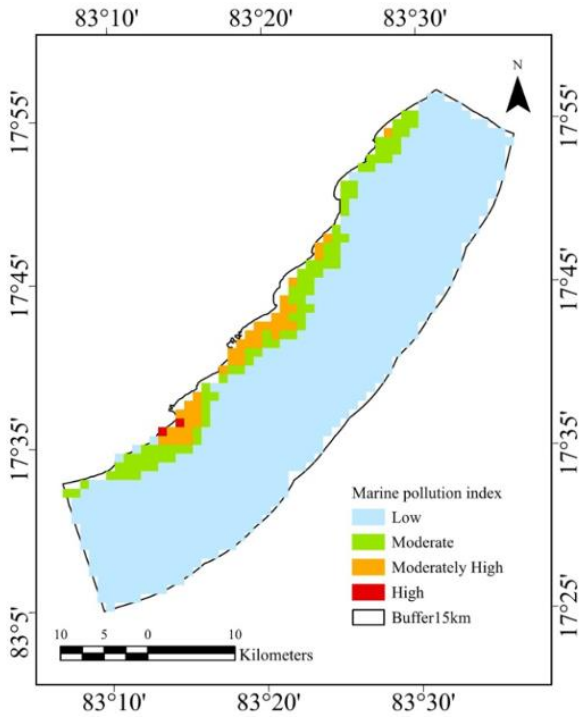

Figure 5. *MPI along the Visakhapatnam coast.*

thermal conditions, suspended matter, and overall pollution intensity along the Visakhapatnam coastal waters (**Fig. 6**).

6.2 Pollution source mapping by administrative sub-district

The inland source mapping further corroborates that among the five coastal administrative sub-districts analyzed, Visakhapatnam Urban, Pedagantyada, and Gajuwaka emerge as the most significant contributors to marine pollution **(Fig. 7)**, as revealed by the weighted integration of seven environmental and anthropogenic parameters. The dominance of these sub-districts is primarily governed by their proximity to drainage networks (0.3324) and industrial port complexes (0.2059), corresponding to buffer distances of 2 km and 5 km, respectively, which received the highest weights in the BWM framework, emphasizing their critical role in facilitating pollutant transport to the coastal environment. Elevated land surface temperatures, dense urban land cover, extensive impervious surfaces, and low slope gradients further characterize these regions, collectively enhancing surface runoff, reducing infiltration, and promoting the accumulation and downstream conveyance of contaminants. The strong spatial correspondence between these high-ranking inland pollution contributors and coastal zones exhibiting elevated MPI values highlights a clear inland to marine pollution linkage, emphasizing the importance of source to sink connectivity in coastal pollution dynamics.

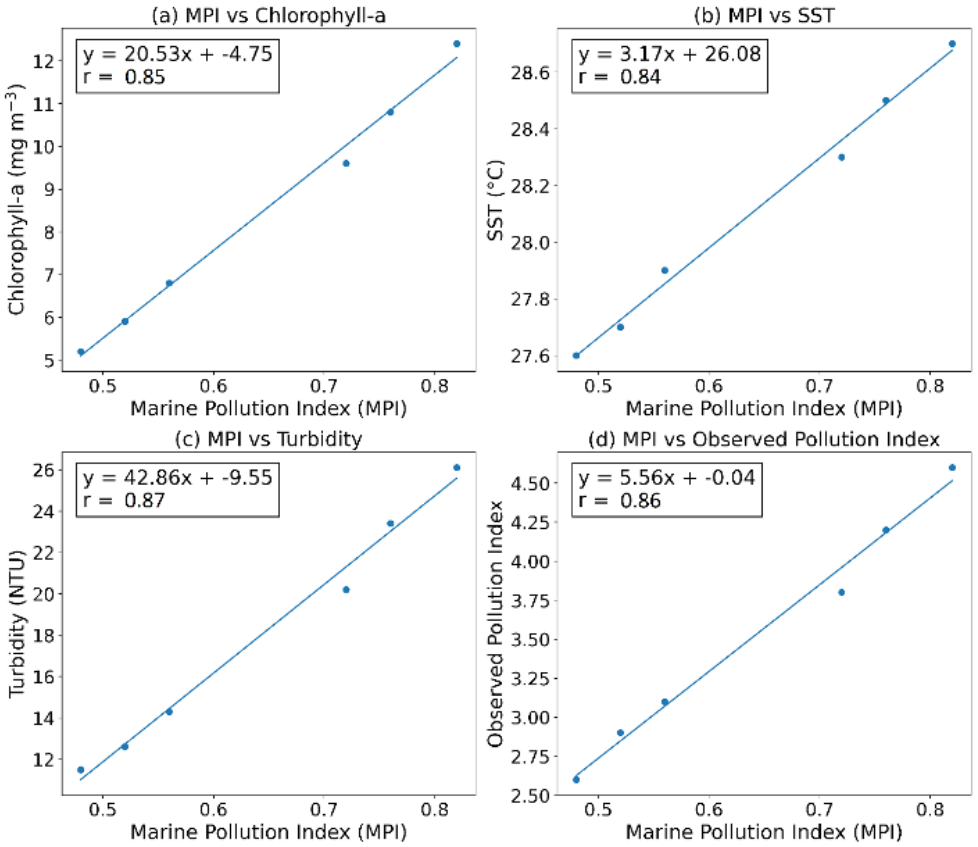

Figure 6. *Relationship between (a) MPI and chlorophyll-a concentration, (b) MPI and sea surface temperature (SST), (c) MPI and turbidity, and (d) MPI and observed pollution index along the Visakhapatnam coast. Strong positive correlations indicate that increasing MPI values effectively represent elevated biological, physical, and overall pollution conditions in coastal waters.*

Comparable land sea pollution linkages have been widely documented across diverse global coastal systems. In rapidly urbanizing river basins such as the Yangtze and Pearl River deltas in China, the Baltic Sea catchment in Europe, and the Mississippi River basin draining into the Gulf of Mexico, urban expansion, industrial clustering, and dense drainage networks have been identified as dominant drivers of nutrient enrichment, sediment loading, and contaminant fluxes to coastal waters (Vörösmarty et al., 2010; Malone and Newton 2020; El-Alfy et al., 2025). These studies demonstrate that low-gradient urban landscapes and engineered drainage systems significantly accelerate the transport of nutrients, heavy metals, hydrocarbons, pharmaceuticals, and emerging contaminants from terrestrial environments to adjacent marine ecosystems. As a result, nearshore waters in these regions frequently exhibit elevated Chlorophyll-a concentrations, increased turbidity, hypoxia, and ecological degradation, mirroring the spatial patterns observed along the Visakhapatnam coast.

Recent global assessments further emphasize that land-based sources account for the majority of marine pollution worldwide, with urban wastewater, industrial effluents, and diffuse runoff from coastal catchments playing a dominant

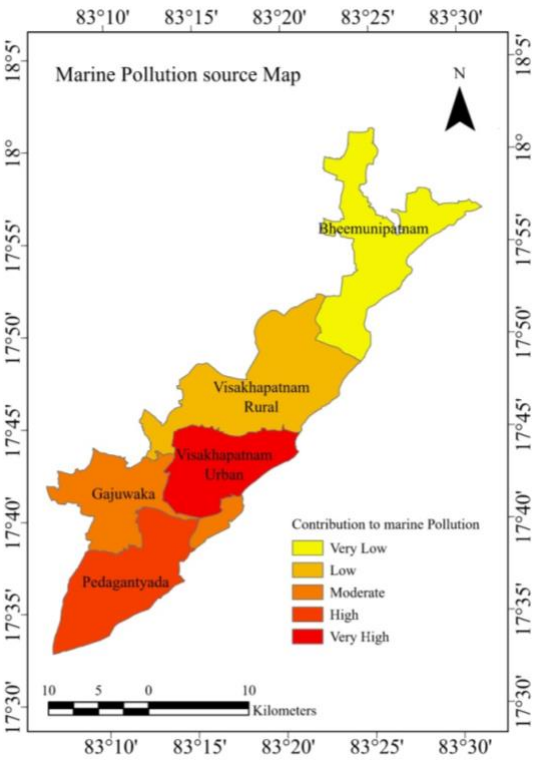

Figure 7. *Administrative sub-district wise pollution source map.*

role (Vörösmarty et al., 2010). Emerging pollutants such as microplastics, antibiotic residues, and antibiotic-resistant bacteria have been increasingly detected in coastal waters downstream of major urban and industrial centers, posing growing risks to marine biodiversity, fisheries, and human health (Zhang et al., 2020). The detection of similar contaminants in the Visakhapatnam coastal region strengthens the relevance of the present findings within this broader global context, indicating that the observed pollution patterns are not regionally isolated but reflect pervasive global trends driven by intensifying coastal urbanization and industrialization.

By integrating marine pollution indices with inland source mapping, the present study adopted a holistic geospatial approach that aligned with globally acceptable integrated coastal zone management (ICZM) and ridge to reef frameworks. Such approaches have been increasingly recommended in global environmental policy and scientific literature to effectively identify pollution hotspots, trace source-to-sink pathways, and support evidence-based coastal planning and mitigation strategies (Halpern et al., 2008). The consistency between this study and global observations emphasizes the broader applicability of this integrated framework for coastal pollution assessment, particularly in rapidly developing coastal regions facing escalating land-based anthropogenic pressures.

7 Conclusion

This study introduces an integrated geospatial framework for marine pollution assessment along the Visakhapatnam coast by coupling satellite derived marine indicators with inland pollution source diagnostics at the administrative sub-district level. By employing the BWM within a MCDM context, the research successfully quantified the relative influence of key environmental stressors. The MPI revealed that southern coastal zones particularly around Gangavaram and Visakhapatnam Ports are under severe ecological pressure due to proximity to industrial clusters and dense drainage outfalls. This marine stress pattern is reflected in inland, where administrative sub-districts such as Visakhapatnam Urban and Pedagantyada emerged as dominant contributors due to urban heat islands, impervious land use, and concentrated anthropogenic discharge pathways. The bridging between offshore ecological risk and onshore pollution drivers provided a better understanding of current environmental conditions that often overlooked in conventional assessments. The methodological synergy of remote sensing, GIS data analytics, and BWM-based decision modelling offers an application for coastal pollution in other vulnerable urban coastlines. Beyond academic insight, the findings deliver actionable intelligence for policymakers, coastal regulators, and urban planners by delineating high risk zones. Future research can build on this framework by incorporating real time hydrological and biological datasets (such as species loss and fishery decline), and socioeconomic vulnerability layers to evolve towards a dynamic coastal pollution early warning and response system.

8 Data availability statement

All datasets used in this study are publicly available from open-access repositories. Sentinel-3 OLCI Level-2 Water products used for Chlorophyll-a and Turbidity were obtained from the Copernicus Open Access Hub portal (https://browser.dataspace.copernicus.eu/). Sea Surface Temperature data were sourced from the GHRSST MUR Level-4 dataset, accessible via Earth data portal (https://search.earthdata.nasa.gov/search?q=GHRSST). Land Surface Temperature and slope data were derived from Landsat 8 TIRS from RSlabs portal (https://www.rslab.gr/downloads_lst.html). CartoSAT DEM for Slope and Drainage Density was from Bhoonidhi data portal (https://bhoonidhi.nrsc.gov.in/). Rainfall data were downloaded from the CHRS Data Portal (https://chrsdata.eng.uci.edu/). Vector data on drainage networks and industrial locations were acquired from OSM using the GeoFabrik data portal (https://download.geofabrik.de/asia/india.html).

9 Ethical statements

This study does not involve human or animal subjects. Ethical approval was not required for this research.

10 Conflict of interest

The authors declare that there is no conflict of interest.

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12 Author contributions

Nazeera Begum Pathan: Data curation, methodology, validation, software, visualization, and writing – original draft. Ibrahim Shaik: Conceptualization, formal analysis, and writing

– review & editing. Pandu Brahmaji Rao: Formal analysis, supervision and writing – review & editing.

13 Copyright statement

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